EPSRC
Engineering and Physical Sciences
Research Council

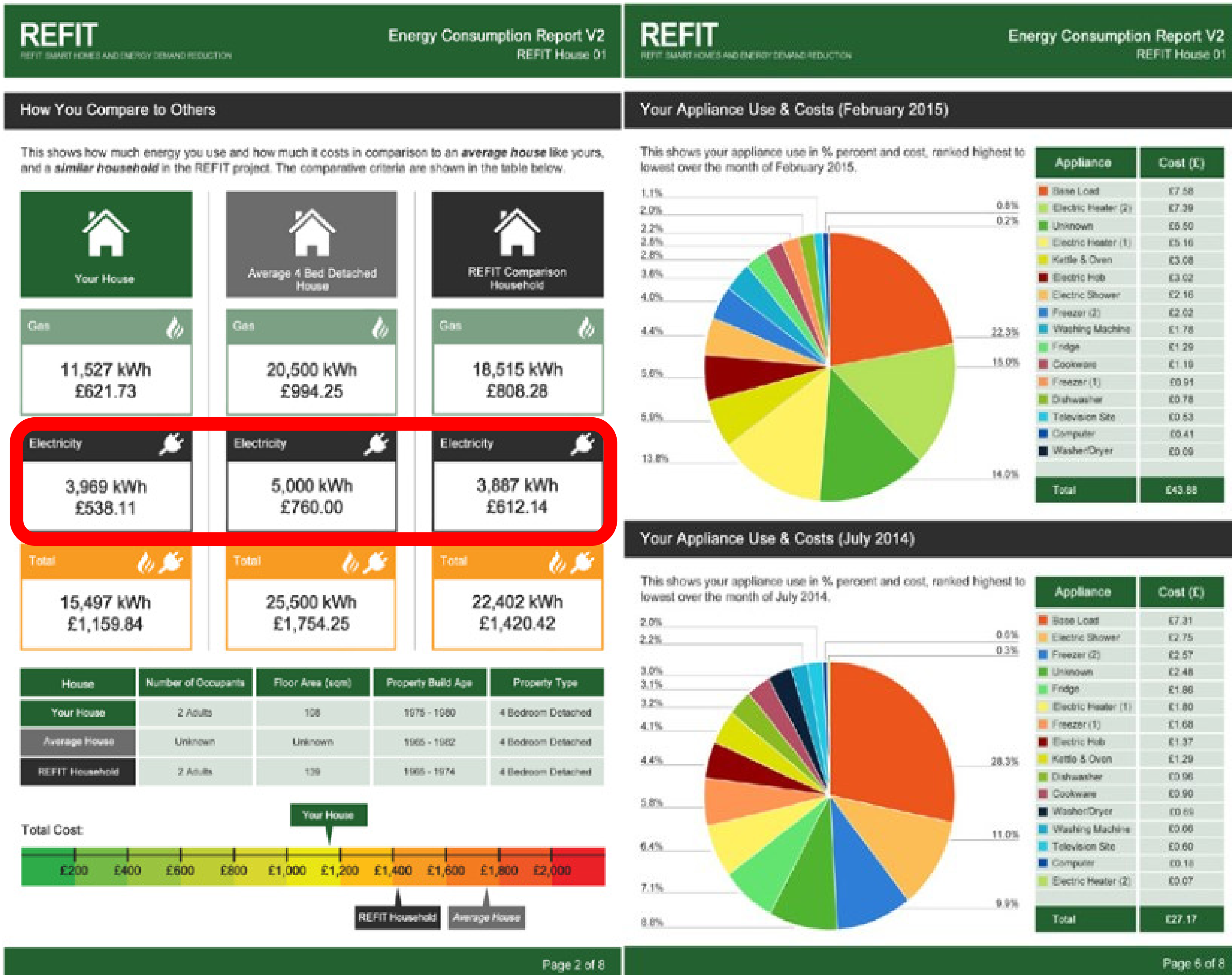
REFIT: Smart Homes & Energy Demand Reduction

University of Strathclyde Engineering

Energy Feedback enabled by Load Disaggregation

Lina Stankovic, Vladimir Stankovic, David Murray, Jing Liao
Dept of Electronic & Electrical Engineering, University of Strathclyde
Contact: lina.stankovic@strath.ac.uk

REFIT Energy Feedback & Findings



1. Comparison with that of the previous month or year => 100%
2. Comparison with other households => 50%
3. Monthly consumption => 65%
4. Daily or weekly consumption => 25%.
5. **Appliance-specific use => 70%**

Load Disaggregation via Non-intrusive Appliance Load Monitoring (NILM)

for smart-meter aggregate load data

- Supervised NILM methods[1,2] — relatively simple, robust, and require short training periods
- Unsupervised method[1,3] —does not require a labelled set of appliances for training
- Training-less method[4] —does not require any prior knowledge of appliances or a training period

Smart electricity meters and **IHDs** tell us about real-time household electricity use, but they don't tell us which appliances were running, nor **what to do about it**.

University of Strathclyde Engineering

Energy disaggregation tells us **when**, **how long** an appliance was used and **how much energy** it consumed, but nothing about **why** it was used.

Beyond NILM

Enhanced feedback on electricity consumption

- advice on non-efficient usage of an appliance
- inform appliance upgrades
- opportunities for (appliance) load shifting
- predict appliance electricity demand
- relating energy consumption to activities in the home, such as cooking or laundering

Appliance Modelling & Informing Energy Savings

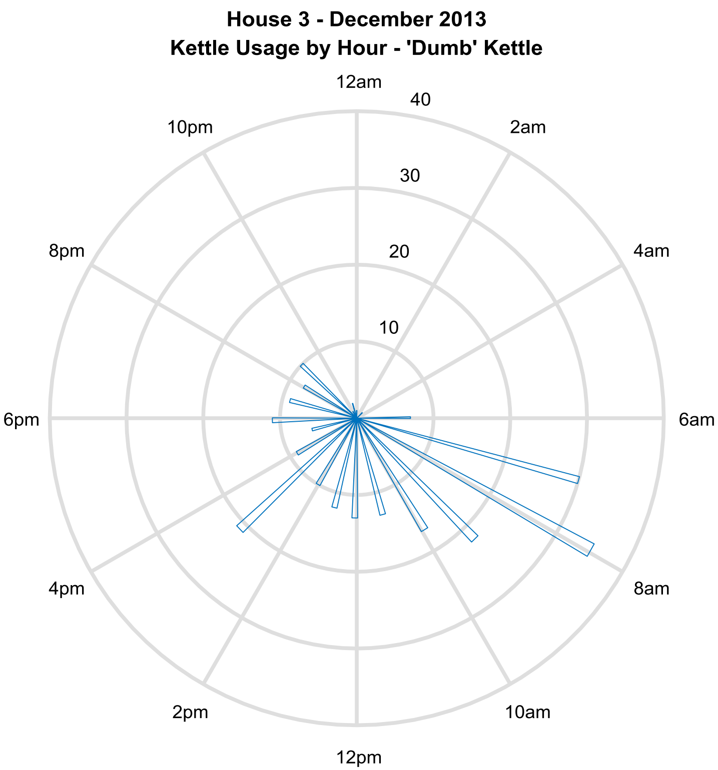
University of Strathclyde Engineering

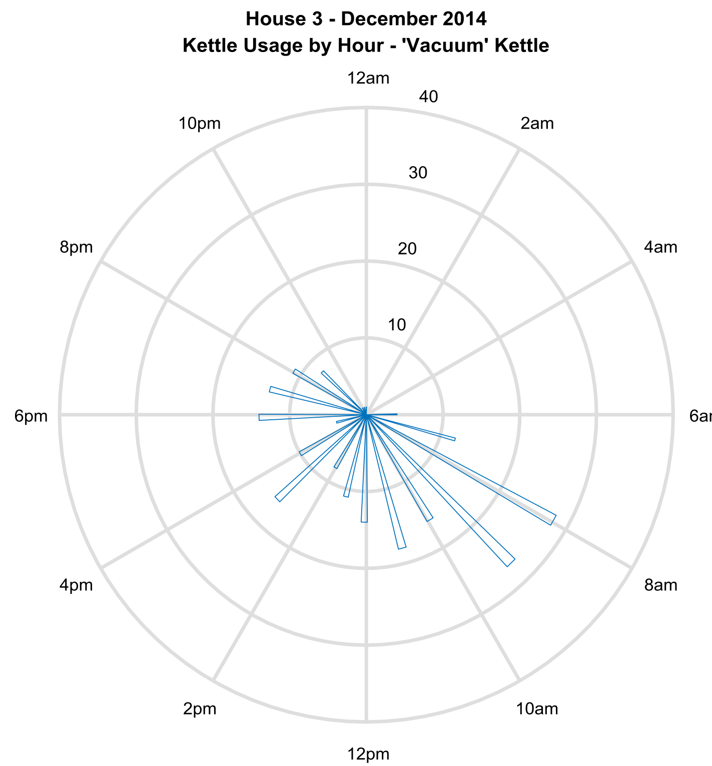
- Kettle: Model inferring the volume of water used purely from disaggregated electricity consumption
- Estimating best usage scenarios to reduce waste

House	Months Recorded	Total Consumption (kWh)	Optimal Volume (mL)	Consumption Above Optimal (kWh)	Savings per Year (kWh)
2	20	255.32	825	126.76	**15.32**
3	20	251.16	550	171.06	**28.85**
5	21	314.66	825	148.85	**17.32**
6	19	273.6	550	122.75	**16.67**
8	18	245.68	550	171.83	**23.41**
9	18	312.36	550	271.31	**73.71**
11	12	182.02	500	83.78	**29.99**
12	15	163.92	825	105.54	**20.98**
17	15	183.63	550	98.98	**16.99**

Informing Appliance Upgrade

Case study of a household upgrading from a standard kettle to a vacuum kettle



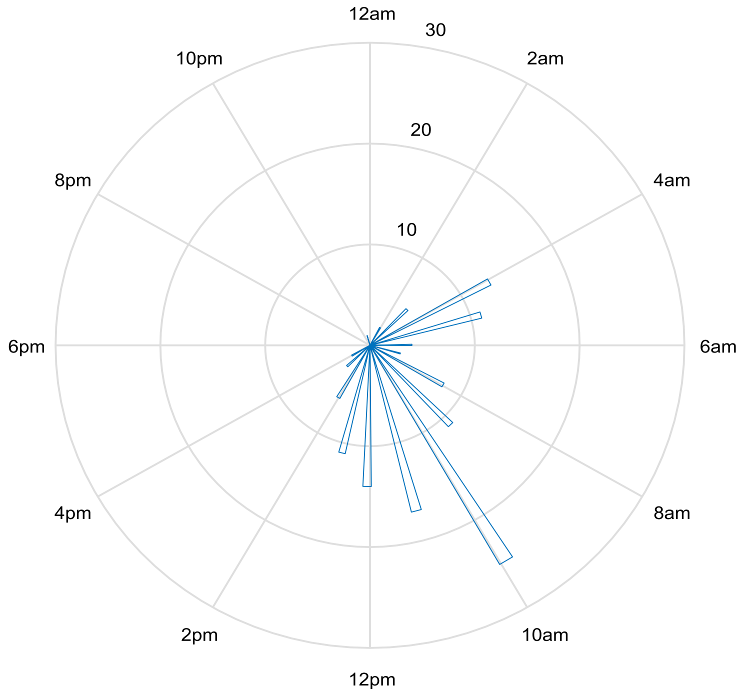


Year	Uses	Consumption (kWh)
Dec 2013 – Standard	238	17.2
Dec 2014 – Vacuum	217	14.8

- Reduction in the number of re-heats
- ~5% reduction per use
- ~14% total reduction
- Continued economical usage style

Load Shifting

House 1 - Washing Machine Consumption by Hour (kWh)



Non Off-Peak uses: 344

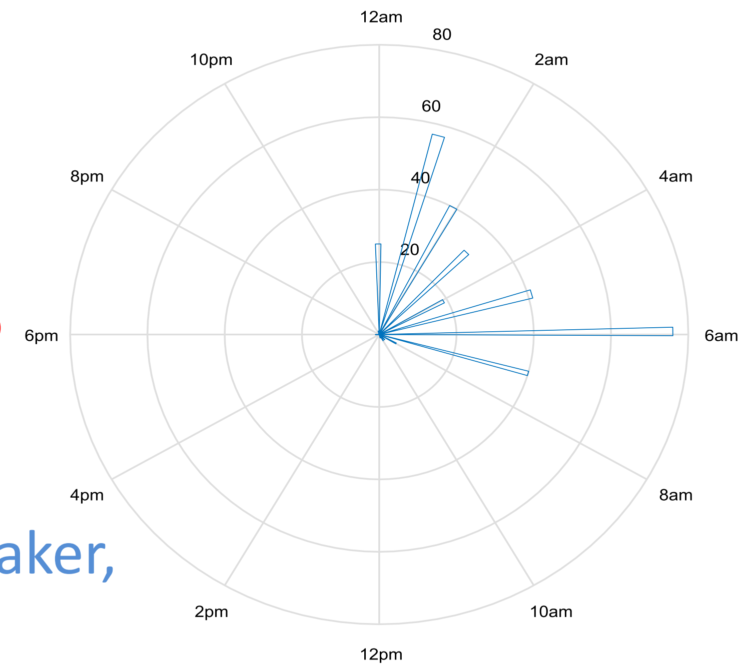
Total load that can be shifted: 99.77 kWh

Day Price: £13.05

Night Price: £7.54

Possible Savings: ~ £5.10

House 8 - Washing Machine Consumption by Hour (kWh)

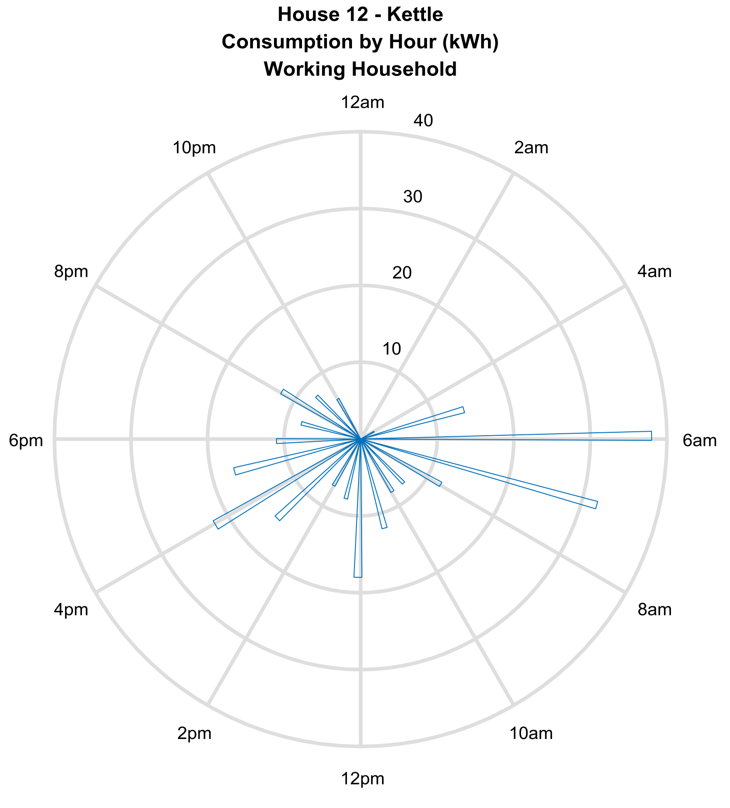


65% of REFIT households would consider adjusting the timing of their appliance use to benefit from a better tariff.

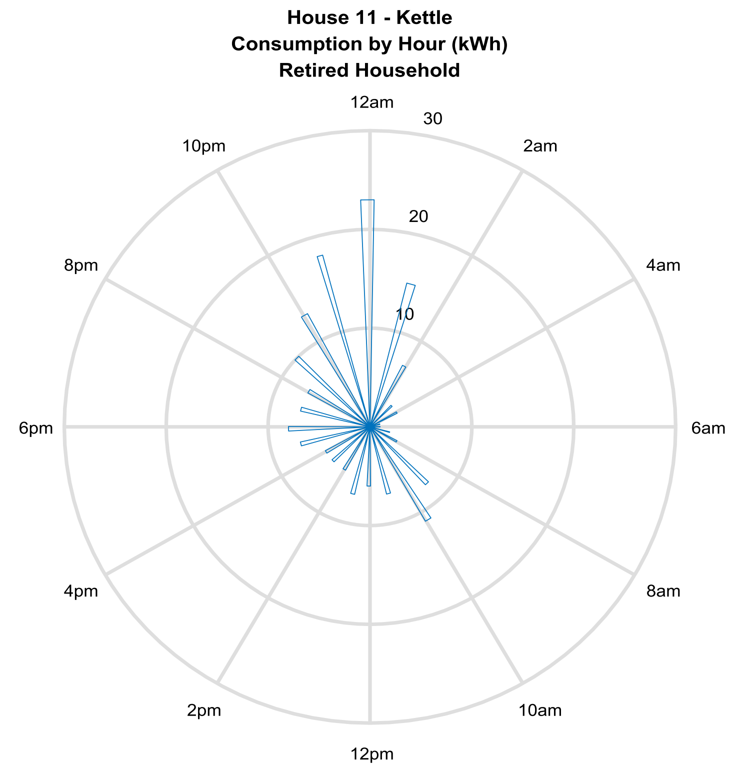
- dishwasher, washing machine and tumble dryer, hobbies, charging devices, bread-maker, computing, and charging their car.

Temporal Patterns of Appliance Use

House 12 (Working)

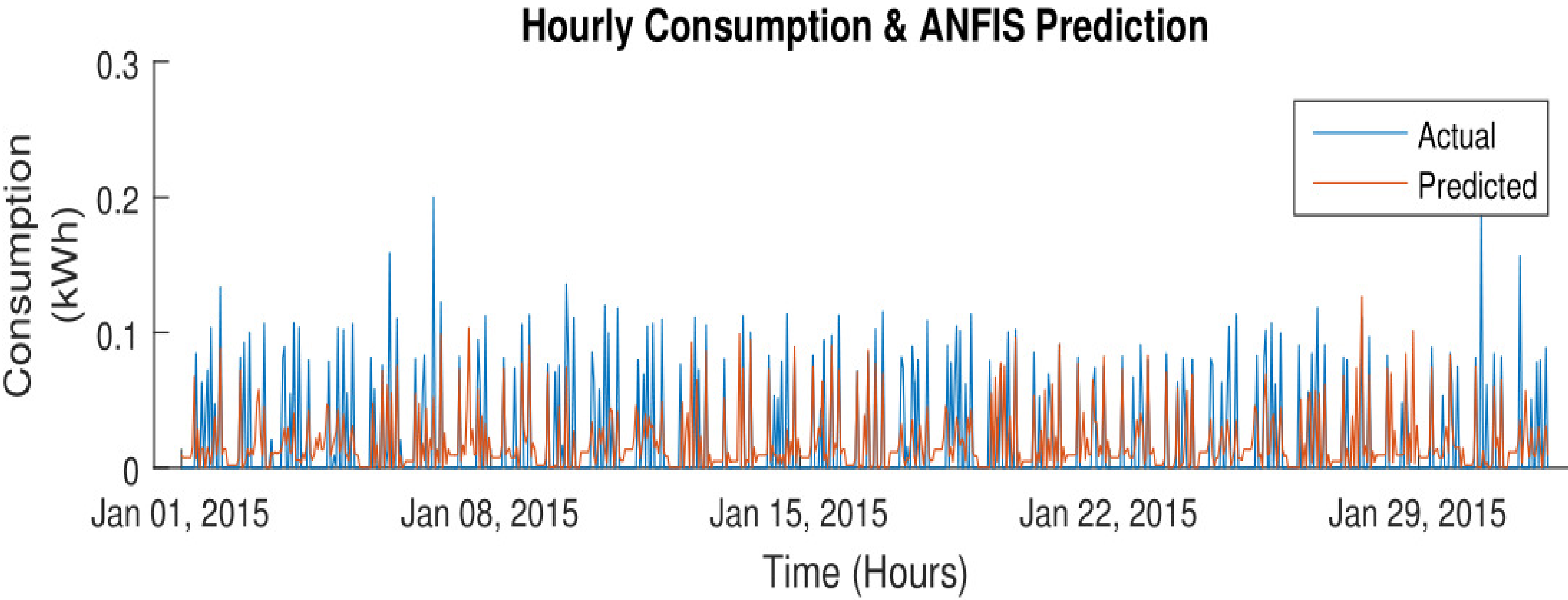


House 11 (Retired)



Kettle Demand Prediction

Deeper understanding and more accurate prediction of appliances will enable more accurate load simulation



Meaningful & salient feedback

Feedback is important *"in making energy more visible and more amenable to understanding and control"*.

Moving away from 'energy-centric' approach in which information feedback directly concerns energy consumption

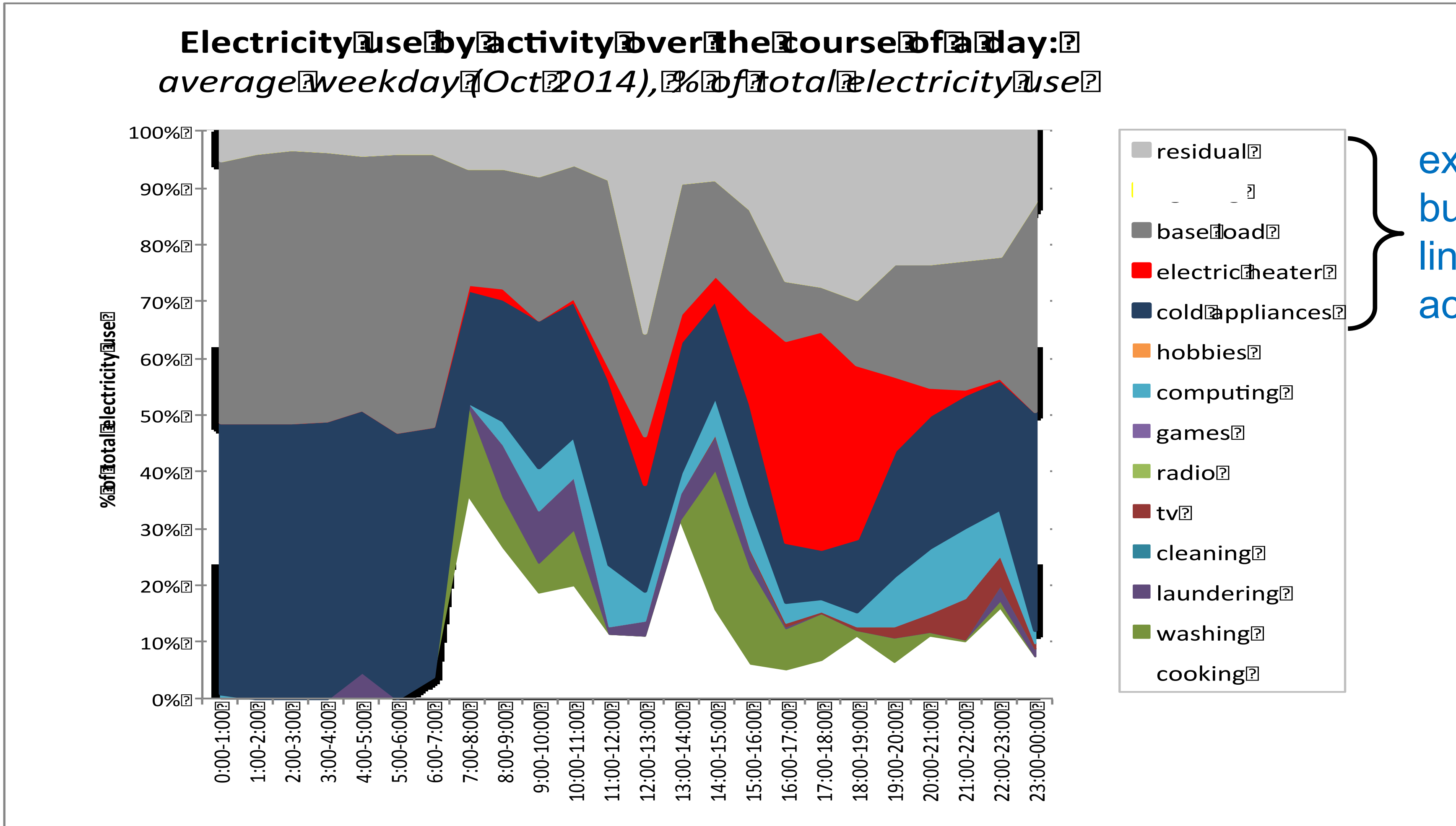
To an 'activity-centric' approach, where the emphasis shifts from energy use to households' lived experience, i.e., routines, habits and activities that constitute the majority of life at home.

Understanding the linkages between appliance use and common activities in the house by integrating **quantitative smart home data** with **qualitative household ethnography** to identify activities at home

Develop, test, and validate a multi-step methodology for making robust activity-based inferences in households

Demonstrate how smart energy meter data can be used to feed back information to households on the time profile of everyday activities in the home and their energy-using consequences

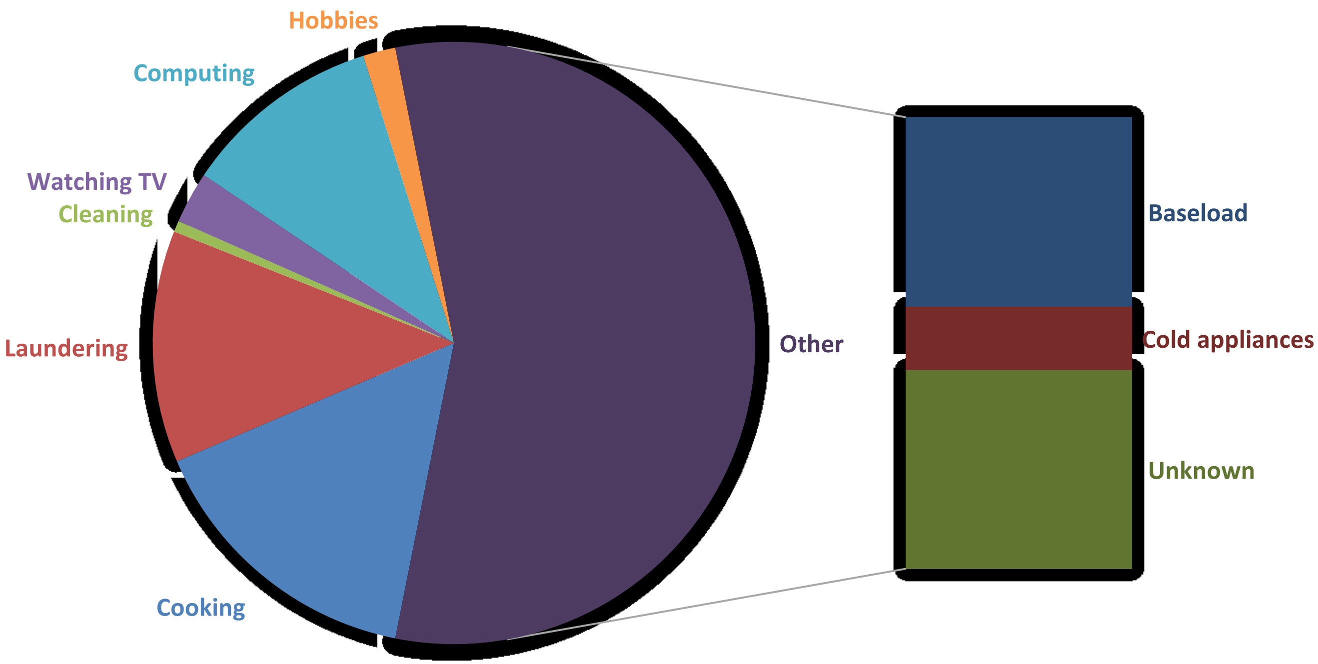
Linkages between Time-use (Activities) and Energy



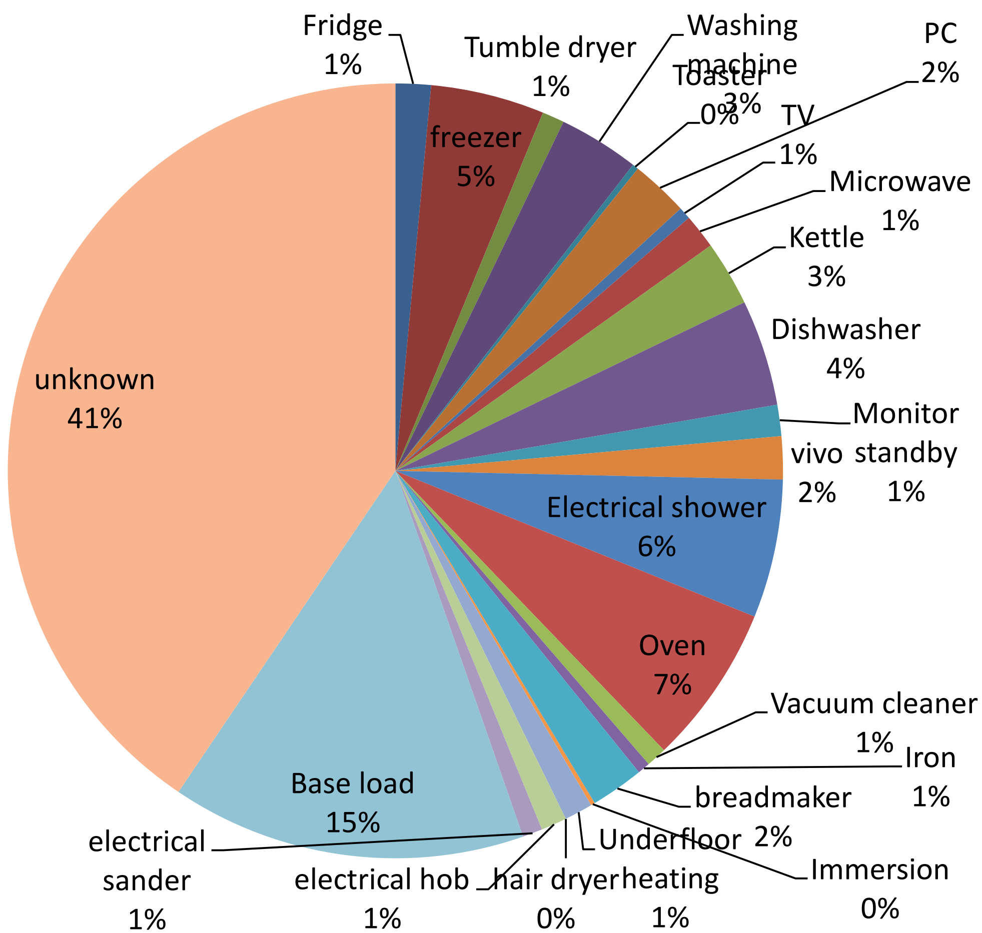
explained but not linked to activities

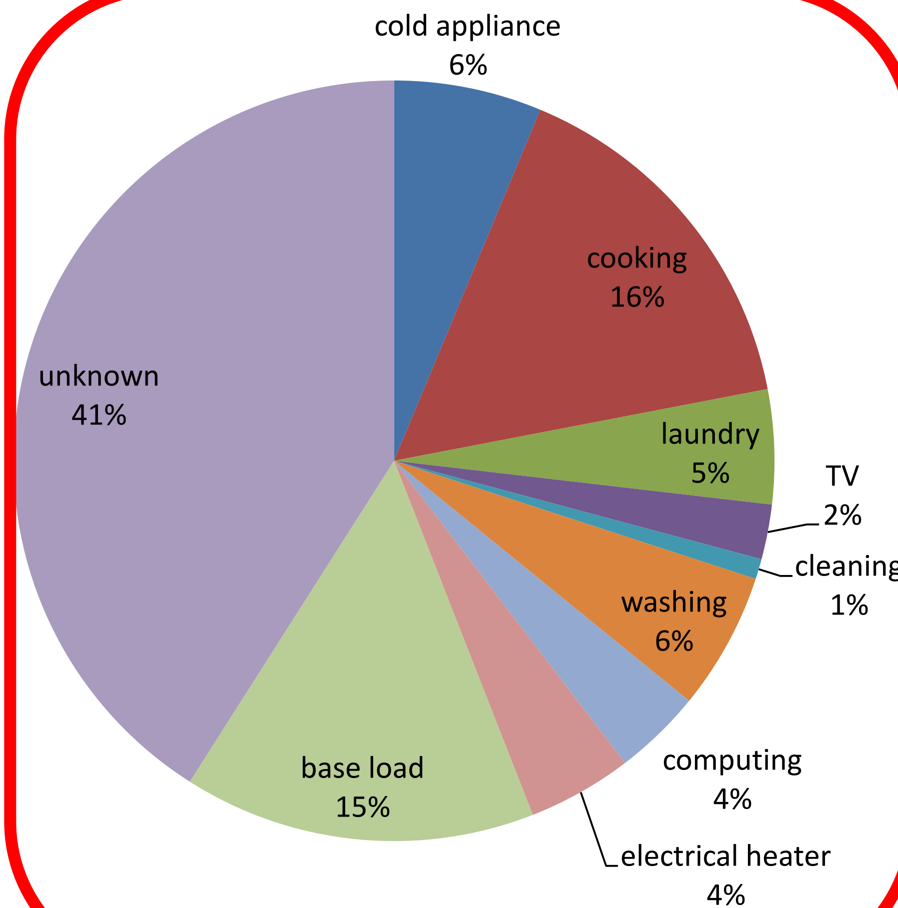
Understanding Energy Demand through Activities

In this household, detected activities can account for almost 50% of the monthly total electricity consumption, with cooking and laundering playing a significant part.



Monthly electricity breakdown





- The total electricity use explained by activity inferences is 33%. The rest is accounted for by lighting, cold appliances, base load, and heating.

NILM-facilitated Energy Feedback

University of Strathclyde Engineering

- Using disaggregated information about the when, duration and energy consumption of each appliance use:
  - Time use statistics to quantify, predict and inform (efficient) appliance use and upgrade
  - Identify opportunities for load shifting of particular appliances & quantify energy savings due to shifting appliance use
  - Understanding electricity demand through the lens of activities by integrating **quantitative smart home data** with **qualitative household ethnography** to identify activities at home

University of
Strathclyde
Glasgow